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Testing the Profitability of Technical Analysis as a Portfolio Selection Strategy

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Abstract

One of the main difficulties in evaluating the profits obtained using technical analysis is that trading rules are often specified rather vaguely by practitioners and depend upon the judicious choice of rule parameters. In this paper, popular moving-average (or cross-over) rules are applied to a cross-section of Australian stocks and the signals from the rules are used to form portfolios. The performance of the trading rules across the full range of possible parameter values is evaluated by means of an aggregate test that does not depend on the parameters of the rules. The results indicate that for a wide range of parameters moving-average rules generate contrarian profits (profits from the moving-average rules are negative). In bootstrap simulations the returns statistics are significant indicating that the moving-average rules pick up some form of systematic variation in returns that does not correlate with the standard risk factors.

Keywords

Stock returns, Technical analysis, Momentum trading rules, Bootstrapping.

JEL Classification C22, C53, Q49

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1 Introduction

The concept of making risk-adjusted economic profits from implementing relatively simple technical trading rules, which derive their buy/sell signals as functions of past prices, has been discussed and implemented in equity, currency and other markets (see, *inter alia*, Brock, Lakonishok and LeBaron, (1992; Jegadeesh and Titman, (1993); Levich and Thomas, 1993; Blume, Easley and OHara, 1994; Osler and Chang, 1995; Chan, Jegadeesh and Lakonishok, 1996, 1999; Hudson, Dempsey and Keasey, 1996; Bessembinder and Chan, 1998; Gencay, 1998; Allen and Karjalainen, 1999; Sullivan, Timmermann and White, 1999; Lo, Mamaysky and Wang, 2000; and for Australian equities see Hurn and Pavlov, 2003; Demir, Muthuswamy and Walter, 2004; Pavlov and Hurn, 2010). There is sufficient evidence in this body of literature to support the contention that technical analysis is a profitable undertaking. This conclusion is intriguing from both a theoretical and practical point of view, because it seems to provide evidence against efficiency in these markets and suggests that investors are able to select a specific trading rule, *ex ante*, from an infinite set of rules and generate excess profits in a real-world implementation.

A common strand which runs through much of the literature on the profitability of technical trading strategies is the data-snooping bias. Lo and MacKinlay (1990) demonstrated that access to a relatively small amount of prior information can have a dramatic impact on statistical inference. This prior information may arise from a number of sources, the most obvious being that tests of the profitability of technical analysis traditionally focus on a small number of trading rules with judiciously chosen parameters. Both the universe of rules that attract attention in the empirical literature and the values of the parameters may be regarded as the result of prior specification search, given that the rules and parameter values that are chosen are the ones that have demonstrated good performance *ex post*. Accordingly, the recent literature on the profitability of technical trading rules has been mainly concerned with the elimination of data-snooping bias and much of the subsequent work in this area uses the Reality Check due to White (2000) in which both parameter uncertainty and rule-selection bias are incorporated into the testing procedure.

This paper concentrates on moving-average (or cross-over) rules.¹ Of course, in practice investors may employ a complex trading strategy in which the informational input of many rules is used and the learning and decision processes of the investor become important for technical analysis (see Hsu and Kuan, 2005). There are, however, a number of advantages to using these trading rules. The first and most obvious reason is that they are one of the earliest documented rules for conducting technical analysis and are still very popular with chartists. Perhaps more important in the context of this research is that the only subjective judgement required to implement the rules is the choice of the moving-average parameters. In order to avoid the data snooping bias, therefore, the distribution of returns over all moving-average parameters will be examined rather than trying to pick a particular set of parameters.

One potential complication arising from empirical tests based on the Reality Check is that trading rules are likely to generate relatively infrequent signals. Consequently for empirical tests based on the Reality Check to have satisfactory power, long series of high frequency observations are required. As a result, much of the empirical research on trading profits tends to concentrate on stock market indices or a small subsection of financial returns such as currencies. The first central contribution of this paper is to overcome potential limitations in time-series data by applying the technical trading rules to cross-sections of stocks and then use the resulting buy and sell signals to form portfolios. The returns to these portfolios form the basis of the tests. The second fundamental contribution of the paper is to propose a set of tests to assess the statistical significance of the portfolio returns for all possible values of the moving-average parameters. A bootstrapping exercise is then undertaken to examine if the distribution of returns to portfolios generated by moving-average rules is consistent with the distribution of returns generated by bootstrapping the time course of the cross-section of stocks.

The rest of the paper is structured as follows. Section 2 describes the dataset used in this research and deals with various methodological points related to the construction of

¹Hsu and Kuan (2005) list 12 classes of simple technical trading rules, namely, filter rules, moving averages, support-and-resistance, channel break-outs, on-balance volume averages, momentum strategies in price and in volume, head-and-shoulders, triangle, rectangle and double tops and bottoms and broadening tops and bottoms.

portfolios based on buy and sell signals generated by moving-average rules. Section 3 sets out the test statistics that will be used to assess the performance of technical analysis as a portfolio selection device. Section 4 outlines the bootstrapping procedures employed to assess the statistical significance of the portfolio returns. The results of the empirical analysis are presented in Section 5. Conclusions are contained in Section 6.

2 Data and Portfolio Construction

The data are obtained from the Australian Centre for Research in Finance (CRIF). The dataset contains monthly observations on prices, returns, dividends and capital reconstructions for all securities listed on the Australian Stock Exchange (ASX) for the period December 1973 to December 2008. The analysis is performed on simple monthly returns defined as the sum of the capital gain and dividend yield taking into account any capital reconstructions.

Table 1 reports the means and standard deviations of returns for equally weighted stocks in different size cohorts. In computing these basic statistics, two different assumptions are employed to handle periods during which there are no reported trades for a particular stock. The first set of statistics assumes that all non-traded stocks are simply assigned the average return based on all the traded stocks in the relevant cohort. In the second approach, the common method for treating missing observations, especially when calculating an index return, namely that of setting the capital gains on a non-traded stock to zero (effectively valuing the stock at the last available market price) is adopted. Return statistics calculated under this assumption are in the columns 4 and 5 of Table 1.

As expected, inferring missing returns with zeros biases the estimate of the mean return downwards (a random stock is expected to provide a positive return). It also implies zero volatility for the periods of non-trading, so the effect on standard deviation estimates is also to be expected. It should be noted, however, that estimating the returns based on traded stocks only ignores exits and de-listings which tend to be associated with distress (although stocks can also exit the database due to mergers). For smaller stocks, in particular, an exit from the database is often preceded by a period of low liquidity

and depressed returns. It is reasonable to expect that the mean return estimates in the second column are biased upward and provide an upper bound on the estimates of the underlying expected return.

Filter CAP	Average Return Inferred		Zero Return Inferred	
	Mean	Standard Deviation	Mean	Standard Deviation
Top 100	1.19	4.97	1.15	4.82
100-200	1.20	4.84	1.18	4.74
200-300	1.07	4.77	1.03	4.63
300-400	0.95	5.08	0.91	4.87
400-500	0.95	5.53	0.87	5.21
500-600	0.94	5.98	0.83	5.46
600-700	1.09	6.65	0.91	6.03
700-800	1.33	7.41	0.99	6.34
800-900	2.66	9.13	1.67	6.84
900-1000	3.54	10.47	1.49	6.53
Top 500				
Equally weighted	1.07	4.75	1.03	4.57
Value weighted	1.12	4.90	0.91	4.44

Table 1: Monthly returns (%) by size for all corporate securities listed on the Australian Stock Exchange for the period January 1973 to December 2008. Size is defined according to the relative ranking based on the price of the last observed trade).

The important conclusion to be drawn from the statistics presented in Table 1 is that for stocks up to the 400-500 cohort, the mean returns and standard deviations for both methods of treating missing returns are relatively close (within 10 basis points of each other). For small stocks (with ranks > 500) the estimates of mean returns are very sensitive to the treatment of missing returns and stock exits. These features are symptomatic of the fact that there is low liquidity in the Australian stock market for small stocks. Consequently, in order to limit the effect of low liquidity on the empirical analysis, in each period the trading rules are applied to the top 500 stocks on the ASX.

Two further criteria are applied in order to weed out thinly traded securities and to control for the fact that over the period covered by the sample, a substantial number of stocks were delisted and exited the database. To be included in the portfolio at time t the security must have no recorded missing observations over the three years prior to portfolio

formation. It is further assumed that investors can anticipate short term de-listings, so that any stocks that exit the database in period $t + 1$ because they have been dropped from the ASX register are not included in the portfolio. In point of fact, this assumption makes no material difference to the results because of the focus on large stocks for which exits are relatively rare. The number of securities that pass the liquidity criteria each month ranges between 273 and 411 with the average being 342 securities.

In this paper, trading signals are generated by moving-average rules. These rules are attractive for their analytical simplicity and lack of ambiguity and are still in widespread use by technical traders.² The rule is based on two moving averages (MA) on the values of the stock. The *long* MA involves heavier averaging and is relatively smooth. The *short* MA uses a shorter averaging window and is relatively volatile. In the folklore of technical traders the former represents the established trend and the latter picks up a change in this trend or may be regarded as a speculative component. In what follows, exponentially weighted moving averages will be relied upon:

$$MA_t(\lambda) = \lambda MA_{t-1} + (1 - \lambda) V_t \quad (1)$$

where V_t is the value of the share at time t and λ is the averaging parameter. Momentum rules based on simple averaging appear to be used more often than rules based on exponentially weighted schemes, although both are used in practice. The motivation for choosing exponential weighting for this analysis is that it provides continuous dependence on the parameter and produces sharper statistical results.³

In order to construct portfolios, buy and sell signals generated by trading rules are used to construct equally weighted share portfolios. Let \mathcal{S}_{it} and \mathcal{B}_{it} be indicator functions for buy and sell signals respectively (set equal to 1 if a signal is generated for the stock i at time t and zero otherwise). In the traditional interpretation of the momentum signals:

$$\mathcal{B}_{t,i} = \begin{cases} 1 & \text{if } MA_t(\lambda_S) > MA_t(\lambda_L) \text{ and } MA_{t-1}(\lambda_S) < MA_{t-1}(\lambda_L) \\ 0 & \text{otherwise} \end{cases}$$

² Lo, Mamaysky and Wang (2000) discuss algorithmic representations for a much wider universe of rules, but whether their interpretations of many of the rules are representative of their use by traders can be questioned.

³This choice is discussed in greater detail in Pavlov and Hurn (2010).

$$\mathcal{S}_{t,i} = \begin{cases} 1 & \text{if } MA_t(\lambda_S) < MA_t(\lambda_L) \text{ and } MA_{t-1}(\lambda_S) > MA_{t-1}(\lambda_L) \\ 0 & \text{otherwise} \end{cases}$$

where λ_S and λ_L respectively are the short and long MA parameters that satisfy the restriction $\lambda_S < \lambda_L$. In other words, buy (sell) signals are generated when the short MA crosses the long MA from below (above).

Denote the time t return on buys and sells by r_t^+ and r_t^- respectively. If N is the total number of stocks available for investment at time t , then the returns on the long (+)/short(-) portfolios respectively are calculated as

$$r_t^+ = \frac{\sum_{i=1}^N \mathcal{B}_{t,i} R_{t+1,i}}{\sum_{i=1}^N \mathcal{B}_{t,i}} \quad (2)$$

$$r_t^- = \frac{\sum_{i=1}^N \mathcal{S}_{t,i} R_{t+1,i}}{\sum_{i=1}^N \mathcal{S}_{t,i}} \quad (3)$$

The arbitrage portfolio is constructed by buying a unit of the long portfolio while financing the purchase by selling a unit of the short portfolio. The return on the arbitrage portfolio is then the difference between r_t^+ and r_t^- unless no buy or sell signals are generated in which case no position is taken. The portfolio is held for 1 month and then sold. The task of subsequent sections is to outline how the statistical significance of any profit to this investment strategy may be assessed.

3 Test Statistics

In this section, a number of test statistics to assess the performance of portfolios chosen on the basis of technical trading rules will be proposed. To simplify the analysis, the value of the short MA parameter is fixed at zero, that is $\lambda_S = 0$. The implication of this choice is that the short moving average is simply the stock price and consequently the test statistics depend only on one parameter, λ_L . The results obtained allowing both parameters to vary are very similar but add considerably to computational burden of the bootstrap simulations that are necessary to generate the distribution of the test statistics.

3.1 Cross-sectional Tests

These tests evaluate the performance of the long or short legs of the portfolio across the cross sectional variation in the universe of stocks at any given time. There are two variants of cross-sectional test.

CS Test

The idea of the CS test is to compare the return on the long or short legs of the portfolio with the return on a randomly selected portfolio of $N_{p,t}$ stocks where $N_{p,t}$ is the number of long or short trading signals generated by the trading rule. Let

$$\bar{r}_{cs,t} = \frac{1}{N_t} \sum_{i=1}^{N_t} r_{t,i},$$

and

$$\bar{\sigma}_{cs,t}^2 = \frac{1}{N_{p,t}(N_t - 1)} \sum_{i=1}^{N_t} (r_{t,i} - \bar{r}_{cs,t})^2.$$

be the estimates of the mean and standard deviation of a portfolio of $N_{p,t}$ stocks randomly selected from the population of available stocks but conditional on the number of stocks in the momentum portfolio. Under the random selection hypothesis, the portfolio based on the rules and the randomly selected portfolio should have the same volatility. The CS test on the long leg of the portfolio is

$$T_{cs}^+(\lambda) = \frac{1}{T} \sum_{t=1}^T \frac{r_t^+(\lambda) - \bar{r}_{cs,t}}{\bar{\sigma}_{cs,t}}, \quad (4)$$

which represents the average difference between the information coefficients of the momentum portfolio and a random portfolio of the same size. The corresponding statistic for the short leg of the portfolio is denoted $T_{cs}^-(\lambda)$.

A large positive (negative) value of the CS test indicates that the relevant leg (long or short) of the portfolio outperforms a randomly selected portfolio. It is expected that subtracting the return on an equally weighted portfolio of shares makes the CS test robust to time-series variation in expected returns. For example, in the presence of expected returns variation, a cross-over rule may generate a large number of trading signals in the periods of high expected returns and few or no signals when expected returns are low.

Subtracting the cross-sectional average (the return on an equally weighted portfolio of all available shares) would take this variation out of the test statistic.

Cross-sectional Arbitrage Portfolio Test (CSA)

Under the null hypothesis that the rule is a random sample from the universe of stocks, both the long and the short legs of the portfolio have the same expected return. This suggests a composite test statistic

$$T_{csa}^+(\lambda) = \frac{1}{T} \sum_{t=1}^T \frac{r_t^+(\lambda) - r_t^-(\lambda)}{\bar{\sigma}_{arb,t}}, \quad (5)$$

where

$$\bar{\sigma}_{arb,t}^2 = \frac{1}{(N_t^+ + N_t^-)} \sum_{i=1}^{N_t} (r_{t,i} - \bar{r}_{cs,t})^2,$$

$\bar{r}_{cs,t}$ is as defined for the CS test and N_t^+ and N_t^- are the numbers of stocks selected into the long and short legs of the arbitrage portfolio.

3.2 Time-series Tests

These tests evaluate the performance of the long or short legs of the portfolio over the 36 months prior to portfolio formation but using the fixed weights selected by the trading rule at the current time. Once again two variants are proposed.

Time-series Test (TS)

The test statistic is

$$T_{ts}^+(\lambda) = \frac{1}{T} \sum_{t=1}^T \frac{r_t^+(\lambda) - \bar{r}_{ts,t}}{\bar{\sigma}_{ts,t}}, \quad (6)$$

where

$$\bar{r}_{ts,t} = \frac{1}{H} \sum_{j=-H+1}^1 r_{t-j},$$

is the average return on the portfolio selected by the rule at time t over the previous H months and $\bar{\sigma}_{ts,t}^2$ is the corresponding sample standard deviation of the portfolio return. Both $\bar{r}_{ts,t}$ and $\bar{\sigma}_{ts,t}^2$ are estimated over the H months prior to portfolio formation using the fixed weights selected by the trading rule at time t . In this analysis, H is set equal to 36 months, the same values as used in the liquidity filter. So $\bar{r}_{ts,t}$ and $\bar{\sigma}_{ts,t}^2$ are the

average return and standard deviation on the portfolio based on rule signals at time t . The corresponding statistic for the short leg of the portfolio is denoted $T_{ts}^+(\lambda)$.

The TS test examines the performance of the long/short leg of the portfolio over the previous 3 years. This test controls for momentum type effects. For example, if the trading rule tends to select past winners in the long leg and past losers in the short leg then the historical mean return will pick up any persistence in the performance of the respective portfolio. It can also be expected that the TS test will be robust to cross-sectional selectivity and variation in the expected return, that is, if the rule tends to pick stock with high (or low) mean returns into a particular portfolio leg. A large value of the TS test would indicate that the trading rule is picking reversals.

Time-series Arbitrage Portfolio Test (TSA)

The test statistic is

$$T_{tsa}^+(\lambda) = \frac{1}{T} \sum_{t=1}^T \frac{r_t^+(\lambda) - r_t^-(\lambda) - \bar{r}_{arb,t}}{\bar{\sigma}_{arb,t}}, \quad (7)$$

where $\bar{r}_{arb,t}$ and $\bar{\sigma}_{arb,t}$ are estimated as the mean and standard deviation respectively of the arbitrage portfolio with the weights frozen at time t and over the 36 months prior to the formation of the arbitrage portfolio.

3.3 A Composite Test

The test statistics above depend on the value of the averaging parameter λ . Since there is no theory to guide the choice of this parameter a composite test is proposed that eliminates the dependence of this parameter by averaging the tests over a range of λ values.

Let $T(\lambda) \in \{T_{cs}^+, T_{csa}^+, T_{cs}^-, T_{csa}^-, T_{ts}^+, T_{tsa}^+, T_{ts}^-, T_{tsa}^-\}$ be the collection of tests suggested thus far. The idea is to smooth these tests using a centred moving average on the interval $[\lambda - 0.1, \lambda + 0.1]$ by computing

$$\tilde{T}(\lambda) = \frac{1}{21} \sum_{i=-10}^{10} T(\lambda + \Delta i)$$

with $\Delta = 0.01$. Now define

$$\bar{\lambda} = \arg \max_{\lambda \in \Lambda} \tilde{T}(\lambda) \quad \underline{\lambda} = \arg \min_{\lambda \in \Lambda} \tilde{T}(\lambda)$$

with $\Lambda = \{\Delta i\}_{10}^{90}$ being a grid of the parameters of the trading rule.

Composite Tests

The composite test statistics are now defined on the the best M trading rules according to the values of $\tilde{T}(\lambda)$ in the neighbourhoods of $\bar{\lambda}$ and $\underline{\lambda}$ given respectively by

$$\overline{\tau}_M = \frac{1}{M} \sum_{i=1}^M \frac{T(\lambda_i)}{\bar{\sigma}_T(\lambda_i)}. \quad (8)$$

In the empirical analysis M is fixed at 10 which, given the selected grid for λ , corresponds to averaging over the interval of length 0.1 centred on the optimal value.

All the test statistics proposed in this section are non-standard and their statistical significance must therefore be established by bootstrapping. A detailed description of the bootstrapping procedure is the subject matter of the next section.

4 Bootstrapping

The fundamental assumption underlying the generation of bootstrapped panels of equity returns is that the returns are generated by time-varying risk exposure to economy-wide risk factors. Recognizing that all factors in these empirical asset-pricing models are proxies for underlying economic sources of risk, the following pragmatic approach was adopted to construct the factors used in a regression model. All the stocks under consideration were ordered on size and sorted into 20 portfolios, each containing the same number of stocks. To identify the appropriate factors to include a principle-component analysis (PCA) of size-sorted portfolio returns was undertaken.

The results of the PCA suggested that a three-factor model was appropriate and the scores of the 3 largest principle components of the unconditional variance-covariance matrix of the returns to these size-sorted portfolios were then computed. As noted in Hurn and Pavlov (2003), the first and second factors obtained from the PCA can easily be interpreted - on the basis of correlations - as the market and the size factors commonly

encountered in the empirical asset pricing literature. It would perhaps have been desirable to be able to interpret the third factor as the excess return on value stocks. Unfortunately, this is not possible as the information necessary to construct value portfolios for the entire period of the dataset was not available. Also note that no additional variation in returns due to industry-specific influences were included by using, for example, collection of returns on equal-weighted industry portfolios.

Factor loadings for each stock are estimated by OLS

$$R_{it} = \kappa_i + \beta'_i f_t + \varepsilon_{it}.$$

No asset pricing theory is imposed on the data so the regression includes a stock-specific intercept. Furthermore, it is assumed that the factors account for all conditional heteroskedasticity and cross-sectional correlations in the data so that the error terms, ε_{it} , in the factor regressions are independent across time and across cross-sections. Based on these assumptions, the generic part of the bootstrapping procedure proceeds by regressing observed returns on the reconstructed factor realizations and saving the residuals, $\hat{\varepsilon}_{it}$. The resampling of these regression residuals then forms the basis of the construction of bootstrap intervals for the individual and composite tests outlined in the previous section.

Three different models are now bootstrapped each differing in terms of the assumptions made about the treatment of the factors.

Model 1: Fixed factor realizations.

In this case the factor realizations are fixed at the values constructed by the PCA.

Model 2: Independent factor realizations.

The factors are re-sampled assuming that the factors are conditionally as well as unconditionally uncorrelated and factor conditional variances evolve according to GARCH(1,1) models.

Model 3: Autoregressive factor realizations.

The factors are assumed to be serially correlated but conditionally independent. The conditional variances of the factors are modelled as GARCH(1,1) processes.

The following steps describe the bootstrap procedure for the most general model (Model 3). The starting point is the estimation of a GARCH(1,1) model for the three dominant factors in stock returns

$$\begin{aligned} f_t &= \rho f_{t-1} + \zeta_t \\ \zeta_t &= h_t \nu_t \\ h_t^2 &= \omega + \alpha \zeta_{t-1}^2 + \beta h_{t-1}^2 \end{aligned}$$

and saving the standardized residuals $\hat{\nu}_t$. Table 2 shows the GARCH models estimates. Since the PCA is applied to centred data, the factor realizations have zero mean by construction.

	Factor 1	Factor 2	Factor 3
Mean Equation			
ρ	0.259 (0.062)	0.115 (0.055)	0.081 (0.052)
Variance Equation			
ω	1.556 (0.656)	0.311 (0.132)	0.062 (0.025)
α	0.183 (0.049)	0.126 (0.048)	0.078 (0.031)
β	0.733 (0.078)	0.597 (0.143)	0.753 (0.092)

Table 2: Parameter estimates for the AR(1)-GARCH(1,1) model of the factors. The numbers in parenthesis are asymptotic standard errors.

Bootstrapping the panel of stock returns requires resampling from $\{\hat{\nu}_{jt}\}$ with $j = 1, 2, 3$ and $t = 1, \dots, T$ and from $\{\hat{\varepsilon}_{it}\}$ with $i = 1, \dots, N$ and $t = 1, \dots, T$. The estimated model parameters from Table 2 are then used with these resampled residuals to construct the bootstrapped realizations of h_t , f_t and R_t .

5 Results

Figure 1 shows the values of the cross-section and time-series tests as a function of the averaging parameter λ . At very small values of λ , the long average is very volatile and the rules generate a large number of trading signals. The resulting portfolios for either the long or short leg include large numbers of shares. Since such rules can be expected to

respond to noise in the data these portfolios resemble random samples from the underlying population of stocks. It is therefore not surprising that the performance of the rules at small values of λ does not differ significantly from that of the equally weighted portfolio of all shares (panel A). It is however interesting to note that the portfolio based on sell signals actually outperforms the portfolio based on buy signals for all values of λ . Setting aside for the moment the considerations of statistical significance this means that the profitable strategy for exploiting the moving-average rules is actually a contrarian strategy, that is it involves buying on a sell signal and selling on a buy signal.

The same pattern is observed in the panel B of Figure 1 which plots the time-series based tests, indicating that this result does not reflect some form of selectivity bias in the spirit of Conrad and Kaul (1998) who argue that the cross-sectional dispersion in mean returns of individual stocks can be an important determining factor in generating profits to technical trading based on momentum rules. The behaviour of the TS tests at low levels of the smoothing parameter indicates that the rules tend to pick time periods when the stocks tend to under-perform relative to the previous 3 years of returns histories, but as will be seen subsequently when bootstrap intervals are generated, the effect is a relatively small one. At very large values of the smoothing parameter the tests become very volatile. This is again easy to understand by noting that the number of trading signals declines dramatically at $\lambda > 0.9$. In this region the average number of signals per period for either the short or the long leg is less than one.

A striking feature of the tests illustrated in Figure 1 is their behaviour in the range of the parameter values $0.5 < \lambda < 0.9$. The CS tests in particular display a very characteristic hump in this area with the apparent maximum for the short rules and a minimum for the long rules at $\lambda = 0.8$. Most interestingly the minimum for the long portfolio and the maximum for the short portfolio are attained at roughly the same parameter value. It may, however, be dangerous to read too much into this appealing feature of the results. It is worth noting that persistence in the performance of the rules can be expected, due to the nature of the parameter dependence. Specifically, the compositions of the portfolios at all points in the neighbourhood of a point are not dramatically different. A small change in λ is likely to generate very few new signals and consequently it is to be expected that

the test statistics depend smoothly on the value of this parameter.

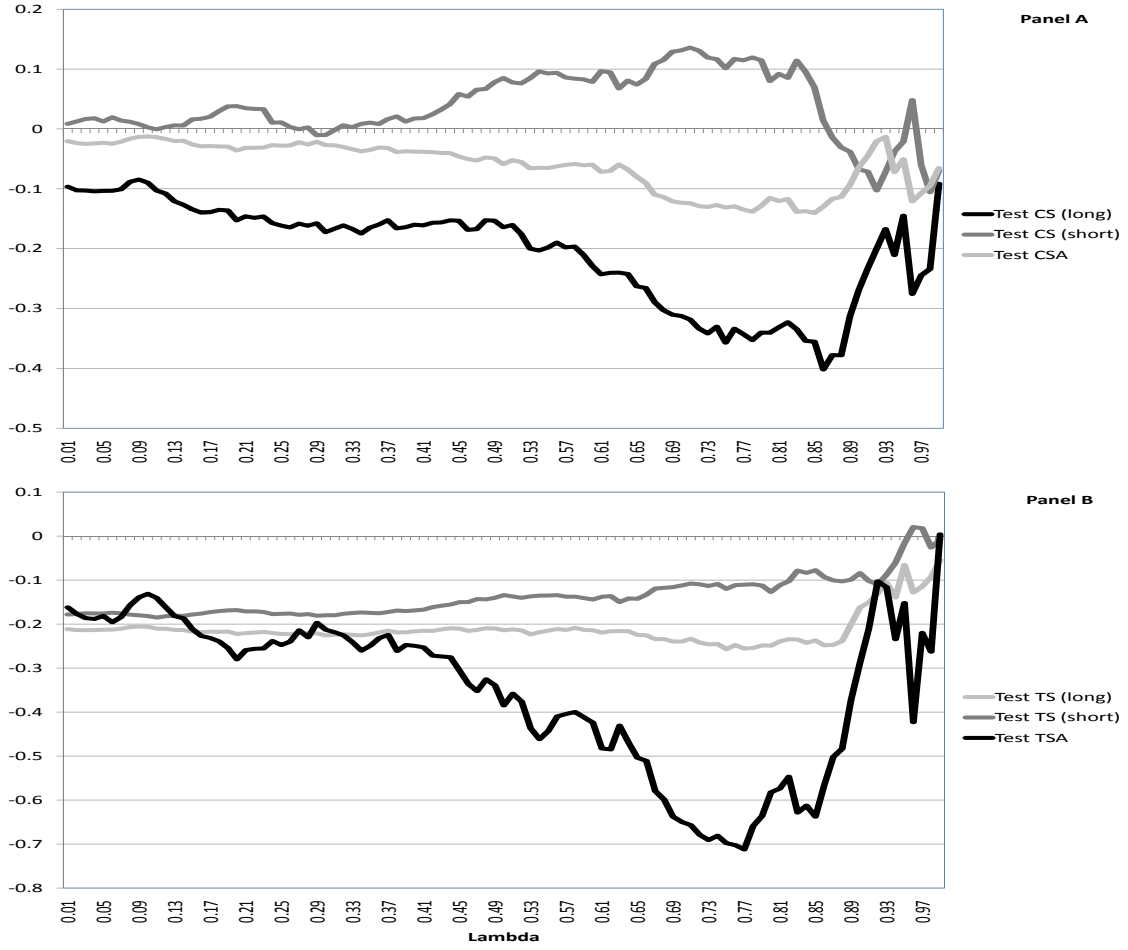


Figure 1: Portfolio profitability tests as a function of the averaging parameter using CRIF ASX stock price data from December 1973 to December 2008. The statistics are calculated on a grid of λ from .01 to .99 with the increment of 0.1.

Figure 2 shows the time-series arbitrage portfolio test (top panel) and the cross-section arbitrage portfolio test (bottom panel) as a function of the averaging parameter together with the 90% bootstrap confidence intervals for the tests. To avoid a proliferation of graphs and tables bootstrap results are graphed only for the arbitrage tests. The most obvious feature of the plot is that none of the bootstrap models can reproduce the size of the performance statistics for the tests on arbitrage portfolio returns, the values of both cross-sectional and time-series tests for arbitrage portfolios are outside of the confidence bounds for substantial regions of the space of the averaging parameter λ .

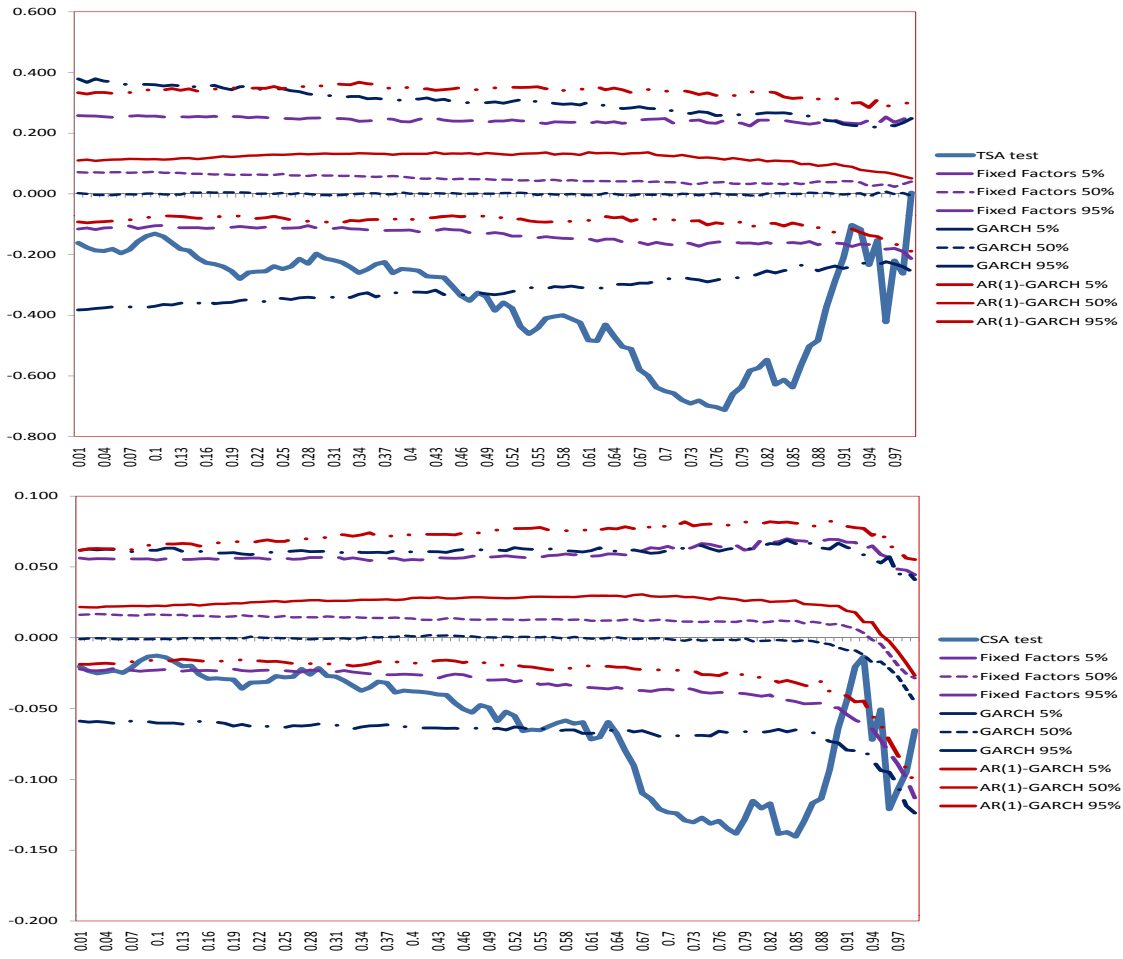


Figure 2: Arbitrage portfolio tests tests as a function of the averaging parameter using CRIF ASX stock price data from December 1973 to December 2008. Bootstrapped 90% confidence intervals for the various bootstrapping models are also shown.

It is interesting to note two additional features of the bootstrap intervals. *First*, fixing the factors at their sample realizations does not lead to sizeably narrower bootstrapped confidence intervals. The simple explanation for this behaviour is that the factor model does not explain a lot of variation at the level of individual stocks. The average R-squared for factor regressions is 16%. This suggests that the likely explanation for the documented behaviour of the test statistics will be found at the level of idiosyncratic returns. *Second*, the median of the bootstrap distribution of both tests is clearly positive when the factors are fixed at their estimated sample realisations. This observation is consistent with the well documented tendency of cross-over rules to produce positive profits when applied to

aggregate indices (see, for example, Brock et al., 1992). Comparison with the median of the bootstrap distribution with serially correlated factors further confirms this impression. When uncorrelated increments are imposed on the factors the median of the bootstrap distribution is very close to zero (except for the cross-sectional test at extreme values of the averaging parameter).

Table 3 shows the values of the composite statistics and the corresponding bootstrapped percentiles. The table reports the composite statistics for the maxima of the short leg of the arbitrage portfolio, minima of the long leg and the minima of the arbitrage portfolio. The maximum CS test $\bar{\tau}_{cs}^-$ is positive which indicates that the portfolio based on a sell signal actually tends to outperform a randomly formed portfolio of the same size, but the sample value of the statistic is well within the range of bootstrap simulations for the GARCH model. The bootstrap percentile for $\bar{\tau}_{cs}^-$ is 75.60% which means that about 25% of the realizations constructed using simulations from the GARCH model are greater than the sample value. However, the AR-GARCH bootstrap provides a tighter upper limit and cannot replicate the size of $\bar{\tau}_{cs}^-$.

The TS tests for both legs of the portfolio indicate that the cross-over rules appear to pick reversals. Both the portfolio based on sell signals and the portfolio based on buy signals under-perform relative to the 3 year period prior to the formation of the portfolio, but the TS test for the long portfolio indicates even greater under-performance. Neither the GARCH nor the AR-GARCH model can explain the under-performance of the short or long legs of the arbitrage portfolio (Figure 1). On balance the results indicate that the arbitrage portfolio is driven to a large extent by the under-performance of the long leg of the portfolio. This is an interesting feature indicating that the return patterns seen in Figure 2 do not hinge on being able to short-sell stocks cheaply. Importantly, both the model with serially correlated factors and the model with no autocorrelation have trouble reproducing the pattern of arbitrage profits seen in the data. The GARCH(1,1) bootstrap percentiles for the arbitrage statistics are of the order of 2%. The AR(1)-GARCH(1,1) bootstrap which appears to be more empirically plausible has bootstrap percentiles considerably less than 1%.

	CS Long τ_{cs}^+	CS Short $\bar{\tau}_{cs}^-$	CS Arbitrage τ_{csa}	TS Long τ_{ts}^+	TS Short $\bar{\tau}_{ts}^-$	TS Arbitrage τ_{tsa}
Data	-0.2478	0.0483	-0.0799	-0.2145	-0.1108	-0.4070
GARCH(1, 1) Bootstrap Intervals						
95%	0.083	0.118	0.049	0.066	0.078	0.231
50%	-0.012	0.001	-0.005	0.011	0.019	-0.018
5%	-0.126	-0.100	-0.061	-0.046	-0.043	-0.317
Bootstrap Percentiles	0.20%	75.60%	2.10%	0.10%	0.30%	2.20%
AR(1)-GARCH(1,1) Bootstrap Intervals						
95%	0.087	0.033	0.061	0.058	0.032	0.271
50%	0.027	-0.028	0.024	0.013	-0.014	0.107
5%	-0.040	-0.093	-0.016	-0.028	-0.065	-0.063
Bootstrap Percentiles	0.10%	98.20%	0.10%	0.10%	0.20%	0.10%

Table 3: Data values and bootstrap intervals for the composite statistics. The values in the row titled 'Data' are the sample values of the composite tests. The section titled GARCH(1,1) reports the 10% confidence interval, the median (50%) and the exact percentile of the data value in bootstrap simulations for the GARCH model. The section AR(1)-GARCH(1,1) reports the corresponding values for the AR(1)-GARCH(1,1) model. The intervals are based on 10,000 replications.

To check if the contrarian returns pattern is stable over time, the full sample was split into two equal length sub-periods; the first from December 1973 to February 1992 and the second from March 1992 to December 2008. Figure 3 illustrates the pattern of average returns across these sub-periods. Although the magnitude of contrarian returns appears to be much smaller in the second sub-period, the general pattern of the arbitrage profit is very similar across both these periods. When the long and short legs are examined separately, the most obvious change in behaviour is in the returns on the portfolio formed on the sell signals. A possible explanation for this behaviour of the average returns across sub-periods is provided later.

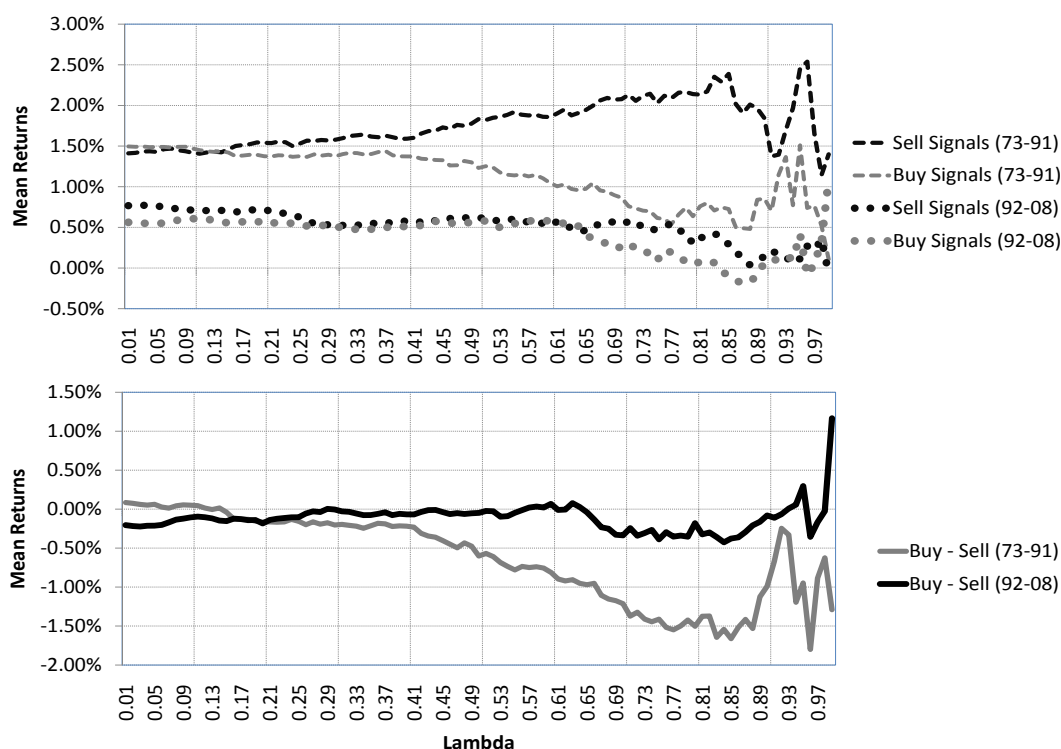


Figure 3: Returns to portfolios constructed by moving-average rules in two sub-samples; December 1973 to February 1992 and March 1992 to December 2008.

At this stage it is necessary to comment on the strong positive autocorrelation observed in the PCA factors reported in Table 2 and the implications of this for portfolio profitability. As the factors are constructed from returns on size portfolios, significant autocorrelation is unusual. The most likely source of the correlation is trading non-synchronicity. Some of the stocks especially in the lower size cohorts may not trade daily, meaning that the measured monthly returns may include an overlap if no valid observation was available for the last business day of the month. When the returns are aggregated into an index this overlap manifests itself as positive autocorrelation.

The positive serial correlation in factor returns actually makes the contrarian profits more difficult to explain. Consistent with intuition positive serial correlation tends to predict positive profits to moving-average rules and helps explain how the results generated using portfolios of stocks can be consistent with the common finding that cross-over rules generate positive profits when applied to stock indices. The natural question to ask is whether

the results are driven entirely by the idiosyncrasies in the trading patterns of small stocks. To check this conjecture, the sample of 500 stocks was split into two equal size groups; the first containing the largest 250 stocks and the latter containing the remaining smallest 250. The trading rules were then applied separately to these size groups.

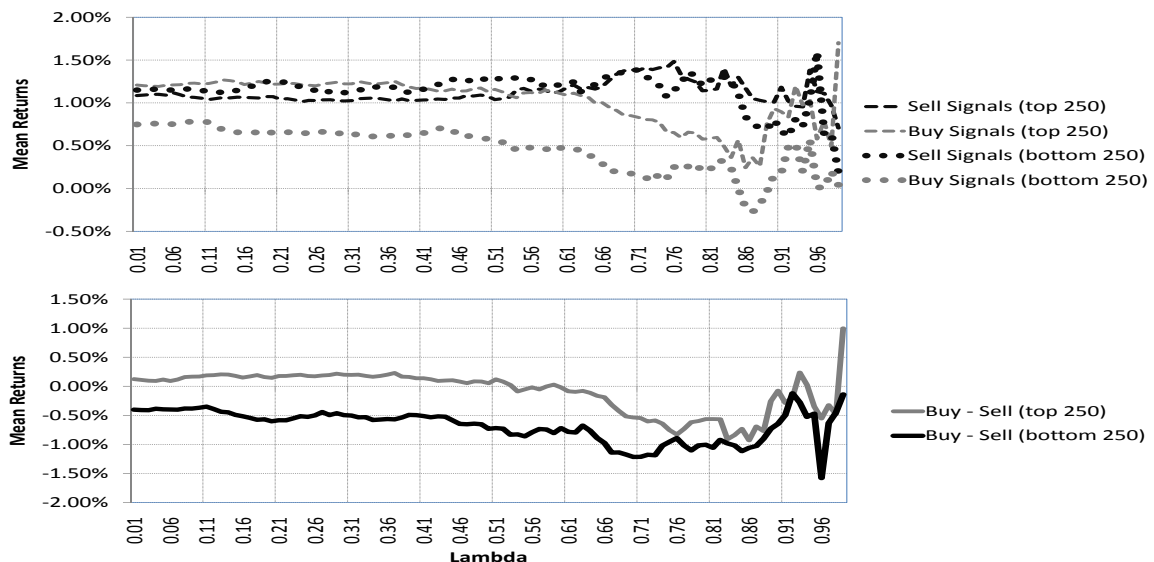


Figure 4: Returns to portfolios constructed by moving-average rules applied separately to the largest 250 stocks and the smallest 250 stocks.

Figure 4 shows the average returns on the long and short legs of the portfolio and the full arbitrage portfolio for each size cohort as a function of the averaging parameter λ . It is clear that the contrarian profits are observed in both size cohorts. It appears that size or trading irregularities are unlikely to provide an explanation for the returns on the momentum portfolio. Other possible explanations for the profitability of trading rules returns include: behavioural phenomena such as over-reaction, under-reaction and feedback trading; as yet undetermined risk factors, statistical anomalies; and liquidity or trading anomalies. The explanation which is explored in more detail now is that economic fundamentals can account for the behaviour of returns to portfolios based on cross-over rules.

The starting point is the construction of the returns to the portfolio corresponding to the largest contrarian profit over the full sample. The value $\lambda = 0.81$ yields the greatest

profit over the grid of values for λ after smoothing the relationship between the average return on the arbitrage portfolio, using a simple moving average of order 10. For lack of a better term, this portfolio will be referred to as the optimal portfolio. Next, the monthly returns are cumulated into yearly returns (June to June) and the correlations between the optimal portfolio and a number of risk factors, aggregate volatility and some common measures of the state of the business cycles including GDP growth, inflation and interest rates, are examined. The relevant correlations are collected in the Table 4.

	Return Buys	Return Sells	Return Buy-Sells	Return EW Market
Return Sells	0.75			
Return Buy-Sells	0.15	-0.53		
F1 (PCA)	0.86	0.88	-0.23	0.92
F2 (PCA)	-0.47	-0.39	-0.02	-0.59
F3 (PCA)	-0.04	-0.08	0.09	-0.03
REW Market	0.83	0.81	-0.14	
R90D	0.00	0.28	-0.42	-0.05
R10Y	0.03	0.30	-0.42	0.05
Volatility	-0.31	-0.30	0.04	-0.26
Inflation	0.11	0.42	-0.47	0.05
GDP	-0.08	-0.11	0.03	-0.18
PC	-0.26	-0.28	0.08	-0.39

Table 4: Correlations between returns on the cross-over strategy and selected variables. F1 to F3 are the principal component scores of the unconditional sample correlations matrix of the returns on 20 size sorted portfolios. REW Market is the return on the equally weighted portfolio of all listed securities (CRIF). R90D and R10Y are the yields on the 90 day bills and 10 year government bonds respectively (Source: RBA). Volatility is constructed as realized annual volatility using monthly REW Market. Inflation is the annual CPI inflation (ABS) and GDP and PC are the annual growth rates in real GDP and private consumption (ABS, chain volume measures).

The correlation estimates are based on 31 yearly observations (1978 to 2008) and are, of course, very imprecise, but they are nonetheless informative. The returns on the long and short legs of the arbitrage portfolio are strongly correlated with the main principal component score and the return on the broad based index. The arbitrage portfolio returns are more interesting in that their correlations with the factors are small and are even smaller at monthly frequencies. This indicates that the performance of the arbitrage

portfolio is not explained by the exposure to systematic factors in returns. On the other hand the return on the optimal arbitrage portfolio appears to correlate most strongly with the nominal interest rates and inflation. In fact, with the exception of the correlations of the returns with the index, the correlations of the arbitrage return with interest rates and inflation are the strongest correlations between the variables that are considered here.

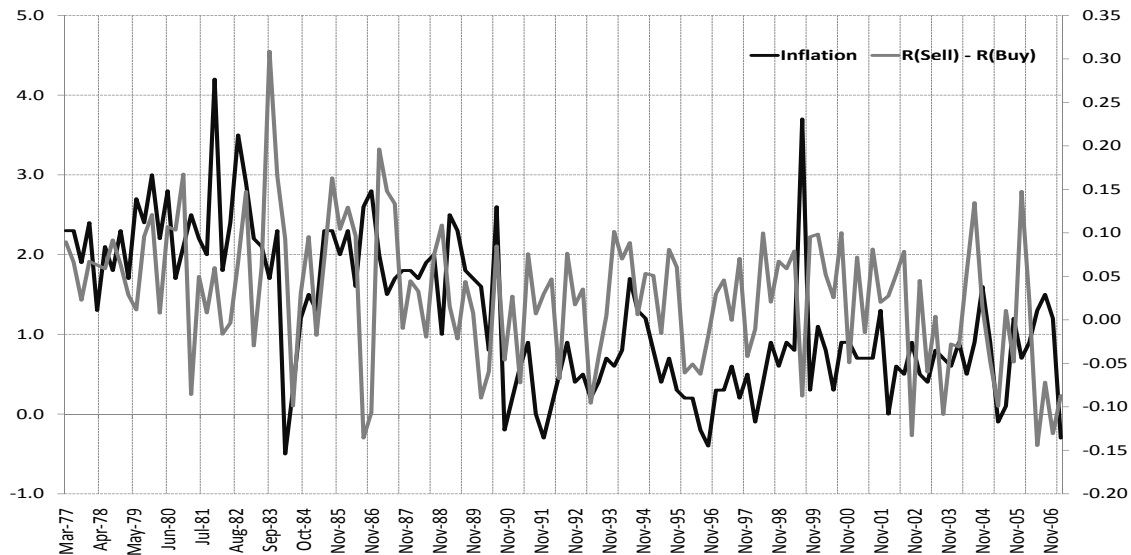


Figure 5: A comparison of quarterly returns on shorting the optimal arbitrage portfolio and quarterly CPI inflation.

Figure 5 plots the quarterly returns on the short position in the arbitrage portfolio and quarterly CPI inflation and illustrates quite clearly the apparent co-movements between the portfolio return and inflation. The returns on the optimal arbitrage portfolio tend to be high in periods of high inflation and low in periods of low inflation. It appears therefore that the performance of the cross-over portfolio can be explained simply as compensation for providing an effective inflation hedge. Although this paper does not suggest or explore an explicit mechanism through which this connection might work, the observation alone is worth making and could provide a fertile avenue for future research.

6 Conclusion

The research reported in this paper has examined the returns to portfolios formed on the basis of the popular moving-average trading rules and some of the aggregate properties of these portfolio returns have been documented. Over a significant range of values for the smoothing parameter used in the specification of the moving-average trading rules, portfolios constructed on the basis of the buy and sell signals generated by the rules appear to generate substantial contrarian profits. Furthermore, simple models of the returns generating process prove inadequate to explain these profits which are largely driven by the abnormal behaviour of the stocks selected in the long leg of the portfolio.

One of the more intriguing results generated by the moving-average trading rules pertains to the returns on the portfolio corresponding to the largest contrarian profit over the full sample. The performance of the arbitrage portfolio is not explained by the exposure to systematic factors in returns but is fairly strongly correlated with nominal interest rates and inflation. Although this paper does not explore these relationships in any detail they provide a tantalizing area for future research.

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